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Integrated Index for assessing operational uncertainty in manufacturing for decision-making

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Orientation: Growing operational uncertainty in manufacturing industries affects decision-making processes.

Research purpose: This study conceptualised and developed an integrated assessment index to measure operational uncertainty in manufacturing.

Motivation for the study: There is a growing need for continuing research to develop integrated indices that fully understand and help manage uncertainty within a firm for its long-term sustainability.

Research design, approach and method: The study is based on a four-step process, which involves identifying theoretical dimensions, measuring indicators, determining the level of individual factors, determining the weight estimates of the factors and composing the manufacturing operational uncertainty index (MOUI).

Main findings: The illustrated index analysis was based on nine operational uncertainty at the external environmental, industrial and firm levels. The results of the present study also confirm that operational uncertainty is a norm in the manufacturing industry with a MOUI = 0.752, indicating the range of futures. This posits that it is difficult to divide these futures into a discrete and exhaustive set of possibilities due to the complexity of conditions at play.

Practical/managerial implications: The study provides essential tools for decision-making, allowing stakeholders to assess performance and enhance continuous improvement efforts by providing a quantitative measure to assess operational uncertainty. It can be applied in order of rank to prioritise response, effects of operational uncertainty on performance and baseline for configuration solutions.

Contribution/value-add: Developing this index is crucial in operations management, as it provides a systematic and simplified approach to assessing, comparing and managing complex data sets.

Keywords: operational uncertainty index; manufacturing; decision-making; range of futures; quantification index.

Introduction

Manufacturing industries face growing operational uncertainty, which influences decision-making processes (Nannapaneni et al. 2017), production stability (Dong et al. 2024; Shi et al. 2023) and operational efficiency (eds. Sridharan, Anilkumar & Vishnu 2019). Alvarez, Afuah and Gibson (2018) argued that the dominant context of uncertainty is based on Knight's (1921) definition of uncertainty as a perceptual phenomenon that exists in conjunction with unique, very complex events or contexts. The author explained that uncertainty cannot be easily assessed or predicted in advance using logical means. Understanding the causes of complexity in manufacturing is challenging (Dhiman, Plewe & Röcker 2019; Wazed, Ahmed & Yusoff 2009), but it can contribute to assessing uncertainty. This, as an effective approach to uncertainty management, encompasses more than simply handling potential risks and opportunities and their respective consequences (Heizmann et al. 2024; Schuh et al. 2024). Lipshitz and Strauss (1997) explained earlier that uncertainty is not a simple or defined notion because of several interconnected causes and complexities that frequently led to circumstances of uncertainty. Knowledge used to mitigate uncertainty is one of the main contextual factors that impact firm decision-making processes and performance (Campello & Kankanhalli 2022; Lipshitz & Strauss 1997). Abou-Chakra (2021) argued that increased transparency of complexity within manufacturing firms can address these complexity challenges. In this context, it is critical that advances are made to continue to understand the levels of operational uncertainty to provide a structured approach to assessing various aspects of manufacturing processes. This enables firms to identify areas for improvement, prioritise the response, and make informed decisions. Studies have shown that indexes can be useful tools to reveal drivers of a particular phenomenon in operations, especially those that seek employee perception of the employees and feedback (Abou-Chakra 2021; Garbie 2014; Mtotywa 2022).

Problem and research gap

There is currently a research gap in studies of the operational uncertainty index with respect to focus, data sources, scope, composition, type of index and application (Table 1). These studies on operational indices focus on operations management or its subfields, but not necessarily on operational uncertainty. These include integrated key performance measurement for manufacturing operations management (Hwang 2020), quality improvement (Mtotywa 2022; Nenadál et al. 2022), manufacturing sustainability index (Gandhi &Thanki 2024) and lean readiness index (Awang, Idris & Zakaria 2022). Furthermore, there is the system readiness index (Sauser et al. 2008), the technology readiness index (Parasuraman 2000; Philipp 2020) and the Industry 4.0 maturity index (Moura & Kohl 2020; Schuh et al. 2020). Abou-Chakra (2021) also developed a complexity index, which helps manage manufacturing problems. There are only a few studies that focus on both operations management and uncertainty (CD) (Abou-Chakra 2021; Gandhi & Thanki 2024; Parasuraman 2000). Furthermore, indices can be developed with conceptual studies (Mtotywa 2022) or empirical studies (Moura & Kohl 2020; Pacchini et al. 2019). Noticeably, most of these research studies are empirically grounded. These conceptual papers focus on theory development (Hulland 2020), while empirical papers on data-driven findings (Banzi et al. 2011) to provide comprehensive insights. De Treville, Browning and Oliva (2023) argued that empirically grounded research emphasises the importance of validating model assumptions and results with empirical data. This is a useful approach as it helps to identify where models align with reality and where they require adjustments (De Treville et al. 2023). Despite this, most of these indices had limited scope or imperfect focus on actual levels of uncertainty. The scope is either firm or industry, and they lack a combined approach of the external environment, industry and firm levels (Sniazhko 2019).

This has led to a disjointed picture of business behaviour and uncertainty and its effect on decision-making, resulting in many different approaches to uncertainty (Hopfe, Augenbroe & Hensen 2013; Sniazhko 2019). Furthermore, most existing measurement and assessment indices have limitations, such as being only limited to one measured uncertainty factor (Olubusoye et al. 2020), descriptive in nature and equally weighted (Moura & Kohl 2020; Nenadál et al. 2022). Additionally, the different studies on index development are also not clear on the format of the constructs (Parasuraman

TABLE 1: Contribution of the literature along with the research gap.

Author	Focus	Data source ** or anticipated*	Scope or detail	Composition			Type of index	Application
	Operations management and operational uncertainty	Employees†(a) or firm performance metrics (b)	Firm/industry External Environment	Indicator contextual flexibility Reflective/formative	Weighted measures	Decision index How much? Low/medium/high	Quantification/ Maturity/Readiness	Scenarios/ configurations/ Decision-making‡
Abou-Chakra (2021)	CD	CD(a)**	Firm	NC	NC	CD	Quantification	CD
Awang et al. (2022)	IM	CD(a)**	Firm	NC	CD	CD	Readiness	CD
Mtotywa (2022)	IM	CD(a)*	Firm	NC	NC	CD	Maturity	CD
Moura and Kohl (2020)	IM	CD(b)**	Firm	NC	NC	CD	Maturity	CD
Nenadál et al. (2022)	IM	CD(a)**	Firm	NC	NC	CD	Maturity	CD
Olubusoye et al. (2021)	IM	CD(b)**	Industry	NC	CD	CD	Quantification	CD
Pacchini et al. (2019)	IM	CD(a)**	Firm	NC	NC	CD	Readiness	CD
Parasuraman (2000)	CD	CD(a)**	Firm	NC	NC	CD	Readiness	CD
Philipp (2020)	IM	CD(b)**	Firms	NC	CD	CD	Readiness	CD
Gandhi and Thanki (2024)	CD	CD(a)**	Firm	NC	CD	CD	Quantification	CD
Schuh et al. (2020)	IM	CD(b)**	Firm	NC	NC	CD	Maturity	CD
Wagire et al. (2021)	IM	CD(a)**	Firm	NC	CD	CD	Maturity	CD
This research	CD	CD(a)	Firm, industry, external environment	CD	CD	CD	Quantification	CD

Source: Mtotywa, M.M. & Mohapeloa, M., 2025, 'Integrated Index for Assessing Operational Uncertainty in Manufacturing for Decision-Making', *Acta Commercii* 25(1), a1426. https://doi.org/10.4102/ac.v25i1.1426

CD, considered; IM, imperfect; NC, not considered.

†, employees including firm representative; ‡, Linked to optimum performance.

2000), which is critical in building constructs from the indicators either as reflective or as formative constructs (Gudergan et al. 2008).

These gaps underscore the importance of continuing research to develop integrated indices that fully understand and help manage uncertainty within a firm for its long-term sustainability. In this research, we advance research on a comprehensive development of the operational uncertainty index. The novelty and contribution of this research is that the index estimates the weights of the factors in an objective rather than the usual assumption of equal weights (Abou-Chakra 2021; Pacchini et al. 2019; Philipp 2020), with those weights using Spearman correlation, which is generally preferable when the sample size is as small as 10, and the normality assumption is violated by exhibiting robust type I error control (Yu & Hutson 2024).

Objectives

This research aimed to develop an integrated operational uncertainty assessment index for improved decision-making in manufacturing industries. Therefore, the objectives of the investigation were twofold: (1) to develop an optimum operational uncertainty index and (2) to explore the application of the operational uncertainty index in the manufacturing industry to improve performance and decision-making.

The remainder of this article is organised into the following sections. Section 2 describes the theory that underpins the development of the index. Section 3 provides the methodological approach, discussing the development of the integrated operational uncertainty assessment index. Section 4 provides a numerical analysis, and Section 5 discusses its application to manufacturing industries. Finally, Section 6 provides a conclusion with theoretical implications of the research, limitations and directions for future research.

Research design and methods

Theory underpinning the development of index

An index serves as a structured tool that quantifies various aspects of operations, enabling firms to evaluate performance, identify areas for improvement, and ensure that operations are in sync with firm strategies (Abdul Hadi et al. 2022). Indices serve as comprehensive tools that integrate multiple indicators into a single coherent framework (Wagenhals et al. 2014), allowing decision-makers to evaluate complex scenarios more effectively (Hwang, Han & Chang 2020; Mozakka, Salimi & Hosseinpour 2024; Mtotywa 2022). This approach not only simplifies the decision-making process but also ensures that decisions are informed by a holistic view of performance and strategic objectives (Chen & Yang 2018). Indices are particularly valuable in contexts where multiple variables must be considered simultaneously, offering a composite measure that can guide operational decisions (Abou-Chakra 2021; Awang et al. 2022; Parasuraman 2000). There are three common types of indices, which are quantification, maturity and readiness (Table 2).

These are the readiness index, maturity and quantification indices. Pacchini et al. (2019) explained that readiness describes the 'state in which a firm is ready to transform to accomplish a task or goal of a phenomenon', while maturity index 'can be used to find out the "as-it-is" state of a firm on the path of transformation' (Wagire et al. 2021:605). The quantification index provides information on the intensity or variability of the phenomenon. The focus for the readiness index is predictive with the lens of future potential, while for maturity, the focus is on the evaluative or developmental stages and descriptive focusing on the magnitude or variability for the quantification index. The time orientation is being future-focused for readiness, present relative to the continuum and present for maturity and quantification index, respectively.

The nature of the measurement is potential and capability for the readiness index, while levels or stages are for the maturity index and numeric quantification for the quantification index. Index aggregation methods can be either additive or geometric and applicable in different phenomena (Gan et al. 2017). The output is generally 0-1 or a percentage of readiness (Awang et al. 2022; Pacchini et al. 2019) and quantification index (Abou-Chakra 2021; Gandhi & Thanki 2024), while it is generally maturity levels or stages for the maturity index (Moura & Kohl 2020; Nenadál et al. 2022). These three types of indices are interrelated, though unique and measure particular contexts.

Methodological approach: Development of the integrated operational uncertainty assessment index

We inductively developed an index to serve as a guide for assessing and comprehending operational uncertainty and assisting decision-making in the manufacturing industries. Operational uncertainty is the focal construct of the investigation (Jaakkola 2020). A series of steps were used to

TABLE 2: Type of indices.

Aspect	Readiness index	Maturity index	Quantification index
Purpose	Assess preparedness for future goals	Assess the developmental stage (progress)	Measure the intensity or variability of a phenomenon
Focus	Predictive (future potential)	Evaluative (developmental stages)	Descriptive (magnitude or variability)
Time orientation	Future-focused	Present (relative to a continuum)	Present
Key question	'How prepared is the system?'	'How developed is the system?'	'How much variability or intensity exists?'
Nature of measurement	Potential and capability	Levels or stages	Numeric quantification
Aggregation method	Weighted average or geometric mean	Summative or weighted scoring	Arithmetic or geometric mean
Output	Readiness score (e.g. 0–1 or percentages)	Maturity level (e.g. stages or scores)	Numerical value (e.g. 0–1 or percentages)

develop the index starting with notation and assumptions that highlight decisions and parameters before these steps.

Notations and assumptions

To define the operational uncertainty composite score, the notation is utilised:

BOX 1: Composite score.

Decision

α Cronbach alpha coefficient for internal consistency reliability

ξ_{sj} Uncertainty assessment factor score for the final individual factors of a firm or business unit, j.

COA_j Composite score of the combined constructs, OAF_j

Parameters

$\bar{a}$ Mean score of indicator

a Individual indicators

k Number of indicators

σ_y^2 Variance of each indicator

σ_x^2 Variance of the total score for observation

ξ Latent variable (dimension)

λ_i Effect of ξ on a_j

δ_i Measures uniqueness

j Firm or business unit

m^{max} Maximum score of assessing the scale

$\overline{Y_{g\xi}}$ Normalised score of the dimension observation or alternative, g for factor (criterion)

ξ, Y_ξ Actual score

Y_ξ^{max} Maximum score from ξ, Y_ξ

Y_ξ^{min} Minimum score from ξ, Y_ξ

s_j Standard deviation

m Total number of factor observations or alternatives.

ρ Spearman rank correlation coefficient

d_i Difference between the two ranks of factors

P_ξ Information content of g_i

w_j Objective weight of Y_ξ

ξ_{sj} Combined dimensions (constructs)

The assumptions used to create the composite score are as follows:

Multidimensional construct. Operational uncertainty is a multidimensional construct that is evident in the external operating environment, at the industrial level and at the individual firm level (Sniazhko 2019).

Sample for empirical data. The sample size must also be considered in determining the sample's credibility, which is critical for effectively validating the model's sample relevance and adequacy. Multiple approaches can be used to determine the sample size, including the central limit theorem (CLT), GPower or the inverse square root method (Kock & Hadaya 2018). The CLT proposes a sample size of n = 30 to n = 60 (Islam 2018; Zhang et al. 2023). A larger sample size tends to improve the rigour of the findings for decision-making (Lund 2023a, 2023b).

Operational uncertainty comprises multidimensional reflective dimensions where the indicators serve to define dimensions (lower-order constructs) (Theodosiou et al. 2019). The approach to the index is that of a reflective model that allows an indicator to be added or excluded from the latent variable. The reflective model equation is described by Edwards (2011) as follows (Equation 1):

$$a_i = \lambda_i \xi + \delta_i \quad \text{[Eqn 1]}$$

where the a_i is the indicator, a_1, a_2 …. a_k k being the number of indicators. ξ is the associated latent variable, λ_i is regarded as the effect of ξ on a_i and δ_i measures uniqueness.

Measurement scores. The score highlights the level of operational uncertainty, with a low score indicating low operational uncertainty, while a high score indicates high operational uncertainty (Courtney 2001; Walker et al. 2003).

Respondent analysis. The relevant sample should include responses from top-level strategic management, process owners, technical specialists and consultants with pertinent experience (Mtotywa, 2022), both inside and outside of the firm. Ideally, the population must reflect the distribution of the sample.

Four-step development

Step 1: Identification of the theoretical dimensions

In research based on conceptualising the focal construct, there are two common approaches to developing indicators (Diamantopoulos & Siguaw 2006). Either the construct can be viewed as the source of its indicators, or the indicators can be viewed as defining characteristics of the construct (Diamantopoulos & Siguaw 2006). In the present research, dimensions were viewed as source indicators with the theory-driven method used for scale development (Spector 2013). The theoretical or empirical dimensions are the nine dimensions. These included external environmental dimensions – geopolitical tensions (GPT), policy and regulatory uncertainty (PRU), the cost of living-driven consumer behavioural change (CLC), pandemic turbulence (PDT) and energy stability and security (ESS). At the industry level, these sources of uncertainty include skills for future industrial work (SFW) and the entrenchment power of large firms (EPL), while at the firm level, sources of uncertainty involve generational work behaviour and ethics (GWB) and process capability and variations (PCV) (Mtotywa 2025). This list of dimensions is not exhaustive, and some sources of uncertainty can be added or existing ones can be replaced.

Step 2: Measurement indicators and determination of the level of individual factors

The developed analysis focuses on nine dimensions of operational uncertainty, each of which contains four indicators. Therefore, the composite score for operational uncertainty consists of 36 items that collectively focus on gaining knowledge of the level of operational uncertainty present in the firm (Mtotywa 2025). To determine the operational uncertainty of individual factors, the interitem correlation of the individual indicators followed by Cronbach's alpha for internal consistency reliability should be performed. For the Cronbach alpha, use Equation 2:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_y^2}{\sigma_x^2}\right) \quad \text{[Eqn 2]}$$

where is the Cronbach alpha, k is the number of indicators, σ_y^2 is the variance of each indicator and σ_x^2 is the variance of the total score for observation. It can be confirmed with a corrected item-total correlation. Upon confirming that the indicators are part of the dimension, the individual dimensions operational uncertainty assessment score, ξ_s, which is calculated for the final individual factors (GPT, PRU, CLC, PDT, ESS, SFW, EPL, GWB and PCV) for manufacturing (which can be a firm or business unit), j: has the following (Equation 3):

$$\xi_{sj} = \frac{\sum_{i=1}^{k} \overline{a}_j}{k x m^{max}} \quad \text{[Eqn 3]}$$

where $\overline{a}$ is the mean score of individual indicators, $\overline{a_{1j}}, \overline{a_{2j}} \ldots \overline{a_{kj}}$ with k being the number of indicators and m^{max} being the maximum score of operational uncertainty, which is five on the 5-point Likert scale. The number of indicators will be based on those present and retained in the model in the reflective model (Hanafiah 2020).

Step 3: Determining the weight estimates of the factors

The next step is to determine the weight estimates of the factors using the importance of the criteria through the inter-criteria correlation (CRITIC) method with Spearman correlation. This is done by analysing the criterion, that is, the importance of empirical factors through the inter-criteria correlation based on the standard deviation (Diakoulaki, Mavrotas & Papayannakis 1995). This is a direct rating with an integrated additive synthesis weighting method (Odu 2019). This is done using the following steps:

Normalisation of the decision matrix, which is a process of transformation of scores into a standard scale that ranges from 0 to 1. During this step, the factors are classified as beneficial or non-beneficial and calculated using the following equation for beneficial factors (Equation 4) and the lower equation for non-beneficial factors (Equation 5):

$$\overline{Y_{g\xi}} = \frac{Y_{g\xi} - Y_\xi^{min}}{Y_\xi^{max} - Y_\xi^{min}} \quad \text{[Eqn 4]}$$

$$\overline{Y_{g\xi}} = \frac{Y_\xi^{max} - Y_{g\xi}}{Y_\xi^{max} - Y_\xi^{min}} \quad \text{[Eqn 5]}$$

where $\overline{Y_{g\xi}}$ is the normalised score of the factor observation or alternative, g for the factor (criterion) ξ, Y_ξ is the actual score, with Y_ξ^{max} being the maximum score and Y_ξ^{min} minimum score within the indicator, observation or alternatives.

Calculate the standard deviation of each factor (criterion) (Equation 6):

$$s_j = \sqrt{\frac{\left(\sum_{n=1}^{m} Y_{g\xi} - \overline{Y}_\xi\right)^2}{m-1}} \quad \text{[Eqn 6]}$$

where s_j is the standard deviation, m is the total number of factor observations or alternatives.

Calculate the Spearman correlation for every pair of factors with Equation 7:

$$\rho = 1 - \frac{6 \sum d_i^2}{m\left(m^2 - 1\right)} \quad \text{[Eqn 7]}$$

where ρ = Spearman's rank correlation coefficient, d_i = difference between the two ranks of factors and m = number of factor observations. Spearman's correlation (ρ) was used to assess monotonic relationships between these factors, regardless of whether there was a linear or nonlinear relationship. Correlation analysis was determined for statistical significance at 5% ($p < 0.05$) and 1% ($p < 0.01$), the direction, whether positive or negative, and strength. For strength, the threshold proposed by Pallant (2020) was used: $0.09 \leq r$ 0.29 (weak), $0.30 \leq r \leq 0.49$ (medium) and 0.5 (strong). Calculate the information content with Equation 8:

$$P_\xi = s_j \sum_{\xi'-1}^{n} \rho\,(g_\xi, g_{\xi'}) \quad \text{[Eqn 8]}$$

where P_ξ is the information content of g_j. Determine the weight estimates with Equation 9:

$$w_j = \frac{P_\xi}{\sum_{\xi=1}^{n} P'_\xi} \quad \text{[Eqn 9]}$$

where w_j is the objective weight of Y_ξ.

Step 4: Manufacturing operational uncertainty index

This step determines the total composite score index for the manufacturing operational uncertainty index (MOUI) and the overall level of operational uncertainty. The total composite score can be formulated as Equation 10:

$$MOUI_j = \sum_{i=1}^{n} \xi_{sij}^{w_i} \quad \text{[Eqn 10]}$$

where $MOUI_j$ is the composite score index of the combined constructs (ξ_{sj}), and w_j is the weighting of the construct – sum to a maximum of 1. The score was used to determine the levels of operational uncertainty. The four levels were explained earlier, as developed by Courtney (2001) on levels of uncertainty and Walker et al. (2003) on decision-making levels. Table 3 indicates levels I to IV.

Ethical considerations

An application for full ethical approval was made to Rhodes University Human Research Ethics Committee and ethics consent was received on 16 November 2023. The ethics approval number is 2023-7527-8189.

Results

Illustrative example

The research focused on nine dimensions for developing the operational uncertainty composite score. This is to determine the level of operational uncertainty in manufacturing based on the four levels of uncertainty. Courtney highlighted four levels of uncertainty: a clear enough future or predictable outcomes, alternative futures, a range of futures and true ambiguity. Level 1 represents the immediate and foreseeable future, while Level 4 represents high uncertainty. Level 2 exists when there are clear paths forward based on a closed set of possible outcomes, and Level 3 occurs when the range of outcomes is larger and hence contributes to a range of futures. To determine this level, a four-step process was employed: (1) Step 1: identification of theoretical dimensions, (2) Step 2: measurement indicators and determination of the level of individual factors, (3) Step 3: determine the weight estimates of the factors and (4) Step 4: determine the total composite score and the overall level of operational uncertainty. The nine dimensions of operational uncertainty contained four indicators. Therefore, the operational uncertainty composite score consists of 36 items (adjusted to 33 based on the results of the measurement model) that collectively focus on gaining knowledge of the level of operational uncertainty present in manufacturing. The final indicators were based on the inter-item correlation of the individual indicators, Cronbach's alpha for internal consistency reliability and measurement model. Table 4 presents the individual dimension score.

TABLE 3: Levels of operational uncertainty.

Level	Description	Score
I	Predictable outcomes	≤ 10
II	Alternative futures	10–40
III	Range of future	41–79
IV	Highly uncertainty (true ambiguity)	≥ 80

Source: Adapted from Courtney, H., 2001, *20/20 foresight: Crafting strategy in an uncertain world*, viewed from https://cir.nii.ac.jp/crid/1130282272229446400 and Walker, W.E., Harremoës, P., Rotmans, J., Van Der Sluijs, J.P., Van Asselt, M.B.A., Janssen, P. et al., 2003, 'Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support', *Integrated Assessment* 4(1), 5–17. https://doi.org/10.1076/iaij.4.1.5.16466

Table 5 presents the weighted estimates for the dimensions. The results show that GWB has the highest weighted average (12.48%), followed by PRU with 12.18% and then PBT with 12.00%.

The lowest are PCV and CLC, which are 9.92% and 9.99%, respectively. The total composite score index the overall level of operational uncertainty was $MOUI_j = 0.752$, indicating the range of futures. As such, due to the complexity of the variables at play, it is not possible to divide these futures into a discrete and exhaustive set of possibilities; yet there are additional alternative futures that are crucial to the decision. Furthermore, the mechanisms that will bring about certain future conditions cannot be simply specified, making it impossible to calculate the precise probability of future events (Courtney 2001; Walker et al., 2003). It is important for the manufacturing firm to understand the levels of uncertainty for effective decision making (Walker et al., 2003).

TABLE 4: The individual score of the dimensions of operational uncertainty.

Dimension	Validity and reliability†	a_1	a_2	a_3	a_4	ξ_{sj} (%)
PCV	Acceptable	4.26	3.72	4.06	4.25	81.5
PRU	Acceptable	3.54	3.83	3.71	3.52	73.0
CLC	Acceptable	4.06	3.86	3.93	3.94	79.0
PDT	Acceptable	4.14	4.02	3.84	3.80	79.0
ESS	Acceptable	-	3.97	3.77	3.69	76.2
GWB	Acceptable	3.57	3.88	-	-	74.5
SFW	Acceptable	3.51	3.51	3.65	3.43	70.5
EPL	Acceptable	3.32	3.85	3.50	3.35	70.1
GPT	Acceptable	4.01	3.56	3.44	3.59	73.0

PCV Process capability and variations; PRU, Policy and regulatory uncertainty; CLC, cost of living-driven consumer behavioural change; PDT, pandemic turbulence; ESS, energy stability and security; GWB, generational work behaviour and ethics; SFW, skills for future industrial work; EPL, entrenchment power of large firms; GPT, geopolitical tensions.

†, Acceptable based on inter-item correlation of the individual indicators, Cronbach's alpha for internal consistency reliability and measurement model.

TABLE 5: Weighted estimates of the dimensions.

Dimension	GPT	PRU	CLC	PBT	ESS	GWB	FW	EPL	PVC	Sum	SD	P_ξ	w_j
GPT	0.00	0.85	0.89	0.81	0.86	0.91	0.94	0.89	0.97	713	0.16	1.14	10.75
PRU	0.85	0.00	0.86	0.82	0.89	0.95	0.81	0.84	0.87	6.90	0.19	1.29	12.18
CLC	0.89	0.86	0.00	0.68	0.68	0.80	0.70	0.59	0.63	5.83	0.18	1.06	9.99
PDT	0.81	0.82	0.68	0.00	0.58	0.82	0.73	0.75	0.76	5.95	0.21	1.27	12.00
ESS	0.86	0.89	0.68	0.58	0.00	0.92	0.50	0.57	0.57	5.57	0.21	1.12	10.57
GWB	0.91	0.95	0.80	0.82	0.92	0.00	0.76	0.72	0.77	6.65	0.20	1.32	12.48
SFW	0.94	0.81	0.70	0.73	0.50	0.76	0.00	0.46	0.36	5.26	0.23	1.18	11.09
EPL	0.89	0.84	0.59	0.75	0.57	0.72	0.46	0.00	0.50	5.32	0.22	1.17	11.02
PCV	0.97	0.87	0.63	0.76	0.57	0.77	0.36	0.50	0.00	5.44	0.19	1.05	9.92

PCV Process capability and variations; PRU, Policy and regulatory uncertainty; CLC, cost of living-driven consumer behavioural change; PDT, pandemic turbulence; ESS, energy stability and security; GWB, generational work behaviour and ethics; SFW, skills for future industrial work; EPL, entrenchment power of large firms; GPT, geopolitical tensions.

Application of the manufacturing operational uncertainty index

The primary motive of a firm is to strengthen and sustain itself, ensuring a good competitive advantage (Agarwal et al. 2022). The development of an index can significantly enhance decision-making processes within a firm by providing a structured and quantifiable means to assess various performance metrics. This, as it provides simplification converting complex dataset into interpretable metrics, can be comparable, allowing for benchmarking across processes, systems, firms, industries or even time periods. The index not only can provide measurable targets for the firms, but it can also assist in identifying gaps and opportunities for improvements. The operational uncertainty index can be applied to manufacturing industries in both developed and developing countries. Firms with a broad perspective on the interplay between levels of uncertainty and the decision-making process improve managerial efficiency. The operational uncertainty index developed by the research can be used for different functions. These include 'rank order for response and resource allocation'. The index can be used to confirm the rank order of the most prevalent operational uncertainty factors to prioritise response and resource allocation. 'Prediction of relationship, understanding the influence of operational uncertainty on the performance of a firm'. Index factors can be used to determine the effect of operational uncertainty on the performance of a firm. This is achieved by understanding whether the factors in the chosen model have an impact, however, slight, on the outcome (Burhnam & Anderson 2002). Furthermore, the size of the effect contributes to understanding the magnitude of the change and the proportion of the overall variance (R^2) in the response that can be attributed to the predictor (Hair et al., 2017). Important predictors can be prioritised using effect size measures. Understanding operational uncertainty leads manufacturing firms to continue to operate in an increasingly unpredictable operating environment (Sibindi & Samuel 2019). It can also be applied in 'baseline for configurations'. A firm's performance can be partially explained by how well its systems fit with each other (Gamede & Mtotywa 2022). The purpose of operational uncertainty configurations is to better understand the intervening factors, and this understanding can be related to operational uncertainty factors and can be used to improve the performance of a firm. The use of configurations possesses predictive potential because, in this context, a firm can use the various viewpoints of knowledge as a mechanism to understand where it is presently situated and to determine where it may seek to place itself in the future. In other words, the use of configurations enables prediction (Ambrosini, Collier & Jenkins 2009).

Conclusion

This research aimed to develop an integrated assessment index for the measurement of operational uncertainty in manufacturing for decision making. The research used nine dimensions at the external environmental level, at the industry level and at the individual firm level to develop the index. This uncertainty index was developed to determine the levels of uncertainty in decision-making. These levels of uncertainty illustrate in this research was range of futures. This indicates that it is difficult to divide these futures into a discrete and exhaustive set of possibilities due to the complexity of conditions at play within manufacturing. The research highlighted how this index can be applied to rank the most prevalent operational uncertainty factors for decision-making, to act as a predictive factor for understanding the influence of operational uncertainty on the performance of a firm and to formulate a baseline for configurations in framework development.

Embracing an operational uncertainty perspective within operational management and researching this topical issue maintains a focus on this salient construct in the face of global challenges that impact the operating environment of companies. By focusing the research within an uncertainty assessment index, this research expands the research on the perceived value that the assessment index has relative to importance, configuration and predictive value. The study's contribution was the development of the operation uncertainty index, which is now known as the MOUI. Manufacturing operational uncertainty index was conceptualised as a tool to quantify and manage the operational uncertainty that manufacturing firms face in their operations. It impacts business decision-making by providing a structured way to determine the prevailing dimensions of operational uncertainty. In so doing, it provides levels of operational uncertainty, allowing the firm to make informed decisions. The MOUI helps firms navigate these dimensions of operational uncertainty by offering insights into potential risks and opportunities. Therefore, it guides decision-makers in understanding and selecting the most suitable response with relevant preventive strategic actions to achieve their goals of sustained performance. The development of this assessment index is critical because there is a dearth of operational uncertainty assessment tools at the level of individual firms that have a broad perspective (external, industry and firm levels).

In this paper, we propose the first version of an operational uncertainty assessment index. This is exploratory research that suggests a line of inquiry for more research in which this point of view might be expanded. This will enable the deployment of the operational uncertainty assessment index by making it accessible, proving its generalisability and maintaining its use in operations management. The suggested future steps are to conduct a quantitative research of top-level strategic management, process owners, technical specialists and consultants with relevant experience both inside and outside the firm to further validate this index. This will strengthen the theoretical and empirical areas that are applicable to firm and may even serve as a basis for generalising the index to other similar industries outside manufacturing.

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Competing interests

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Authors' contributions

M.M. Mtotywa contributed to conceptualisation, methodology, formal analysis, investigation, writing of original draft and writing review and editing process. M. Mohapeloa contributed to conceptualisation, writing review and process and acted as supervisor.

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Data availability

All data generated or analysed during this study are included in this article, and data files are available from the corresponding author, M.M. Mtotywa, upon reasonable request.

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